```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import binom
from scipy.stats import norm
from scipy.stats import poisson
```

```
aerofit = pd.read_csv('/content/sample_data/aerofit_treadmill.csv')
```

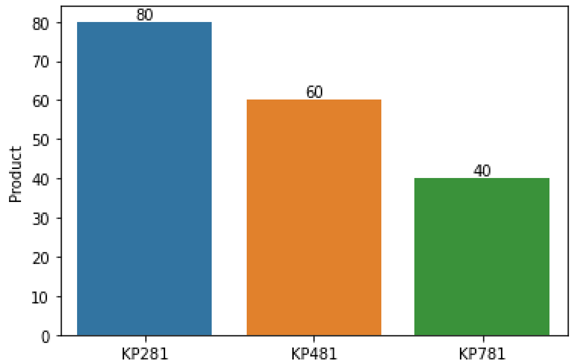
```
aerofit
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

180 rows × 9 columns

```
products_sold = sns.barplot(x=aerofit['Product'].value_counts().index,y=aerofit['Product'].value_counts())
products_sold.bar_label(products_sold.containers[0])
```

```
[Text(0, 0, '80'), Text(0, 0, '60'), Text(0, 0, '40')]
```



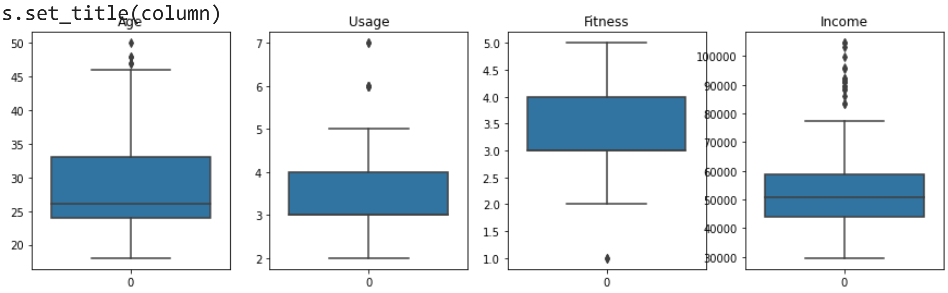
We observe that KP281 is the highest selling product followed by KP481 and KP781

Total Sales Amount 3.25M$

1. For 80 products of KP281 1.2M$
2. For 60 products of KP480 1.05M$
3. For 40 Products of KP781 1.0M$

```
Columns_to_plot = ["Age","Usage","Fitness","Income"]
fig,axes = plt.subplots(1,4,figsize=(15,4))
for column,axis in zip(Columns_to_plot,axes):
```

```
    sns.boxplot(data=aerofit[column],ax=axis)
    axis.set_title(column)
```

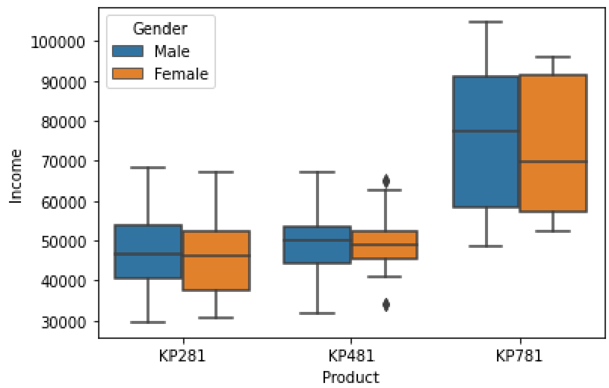


Identifying Outliers among most important Attributes

1. Some customers are earning much more than other customers
2. Some customers might be over planning the number of miles on treadmill compared to what overall customers are planning it. Similarly the same goes with Usage.
3. It is recommended that those who could plan to use much more than others i.e., those outliers should be suggested an advanced machine to avoid machine tearout.

```
sns.boxplot(x=aerofit['Product'],y=aerofit['Income'],hue=aerofit['Gender'])
```

```
<Axes: xlabel='Product', ylabel='Income'>
```



Key Observations

1. Customers with high salary are intended in buying KP781 treadmill
2. Irrespective of the products bought males tend to have higher median of income than females.

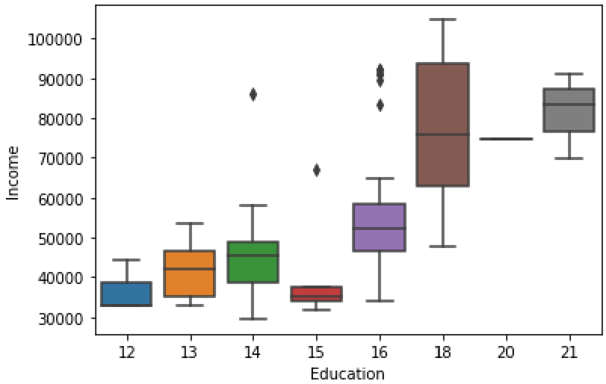
```
sns.histplot(x = aerofit['Age'],hue=aerofit['Product'],multiple="stack",binwidth=5)
```

```
<Axes: xlabel='Age', ylabel='Count'>
```

Age could be a great consice step to fitness so we Understand that customers are mostly aged between 20-30.This can be further investigated to understand the product buying patterns since we don't really get enough patterns here.

```
sns.boxplot(x=aerofit['Education'],y=aerofit['Income'])
```

```
<Axes: xlabel='Education', ylabel='Income'>
```



We are trying to understand customers income in detailed. In which we are trying to interpret that customers with age above 16 are having high incomes compared to other ages which can be a factor of purchasing advanced featured Treadmill KPI781

```
gender_product = pd.crosstab(index=aerofit['Gender'],columns=aerofit['Product'],margins=True,normalize=True)
gender_product
```

Product Gender	KP281	KP481	KP781	All
Female	0.222222	0.161111	0.038889	0.422222
Male	0.222222	0.172222	0.183333	0.577778
All	0.444444	0.333333	0.222222	1.000000

Key Observation

- Total males who purchased tredmills among the list of customers is 57%
- Total females who purchased treamills among the list of customers is 42%
- We see that males and females equally bought the KP281 treadmill
- Males are little more dominant in purchasing KP481 compared to females
- Males are much more dominant in buying KP781 compared to females

```
aerofit_female = aerofit.loc[aerofit['Gender']=='Female']
aerofit_female
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
2	KP281	19	Female	14	Partnered	4	3	30699	66
5	KP281	20	Female	14	Partnered	3	3	32973	66

Filtering out only female customers and understanding their purchases in depth

9	KP281	21	Female	15	Partnered	2	3	37521	85

```
aerofit_female.groupby(['Product','Education'])['Income'].mean()
```

```
Product  Education
KP281    14           43079.666667
         15           35815.500000
         16           48771.315789
         18           67083.000000
KP481    13           46617.000000
         14           44722.000000
         16           52464.428571
         18           56487.000000
KP781    16           71588.500000
         18           75634.750000
         21           69721.000000
Name: Income, dtype: float64
```

We clearly see that KP781 which is advanced treadmill is bought by only those females whose average income is high and also from the previous observation we understand that customers above age 16 and above tend to have more income compared to other ages which can be further understood by buying behaviour here.

```
aerofit_male = aerofit.loc[aerofit['Gender']=='Male']
aerofit_male
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47
7	KP281	21	Male	13	Single	3	3	32973	85
...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

104 rows × 9 columns

```
aerofit_male.groupby(['Product','Education'])['Income'].mean()
```

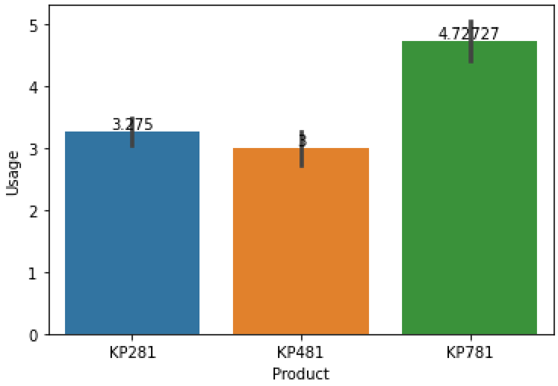
```
Product  Education
KP281    12           38658.000000
         13           36763.000000
         14           46901.250000
         15           33541.500000
         16           49345.800000
         18           68220.000000
KP481    12           32973.000000
         13           53439.000000
         14           41448.818182
         15           67083.000000
         16           52837.058824
KP781    14           67282.000000
         16           69050.615385
         18           81400.066667
         20           74701.000000
```

```
21          87151.000000
Name: Income, dtype: float64
```

We clearly see that the basic treadmill is being purchased by all the age groups and the one with advanced features is only being purchased by high income age groups.

```
avg_usage_male = sns.barplot(x=aerofit_male['Product'],y=aerofit_male['Usage'],estimator='mean')
avg_usage_male.bar_label(avg_usage_male.containers[0])
```

```
[Text(0, 0, '3.275'), Text(0, 0, '3'), Text(0, 0, '4.72727')]
```

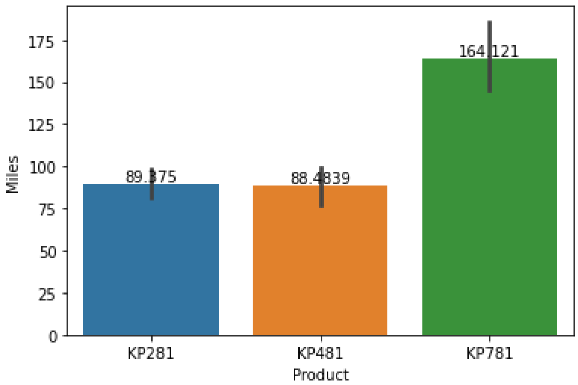


Key Facts

1. Males who bought KP781 have planned more average usage per week among all the types of treadmills
2. Intrestingly we see that the basic treadmill KP281 has got little more avergae usage compared to KP481

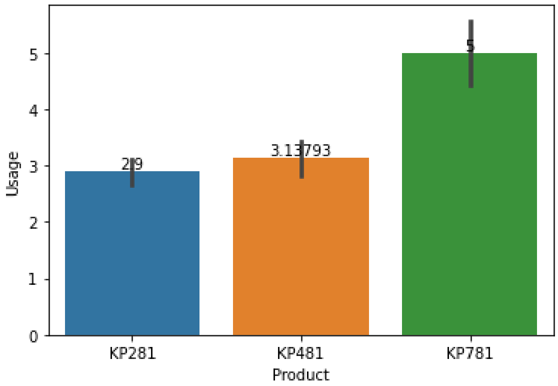
```
avg_miles_male = sns.barplot(x=aerofit_male['Product'],y=aerofit_male['Miles'],estimator='mean')
avg_miles_male.bar_label(avg_miles_male.containers[0])
```

```
[Text(0, 0, '89.375'), Text(0, 0, '88.4839'), Text(0, 0, '164.121')]
```




```
avg_usage_female = sns.barplot(x=aerofit_female['Product'],y=aerofit_female['Usage'],estimator='mean')
avg_usage_female.bar_label(avg_usage_female.containers[0])
```

```
[Text(0, 0, '2.9'), Text(0, 0, '3.13793'), Text(0, 0, '5')]
```

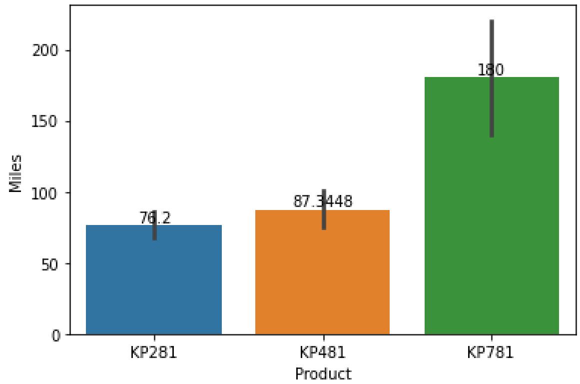


KeyFacts

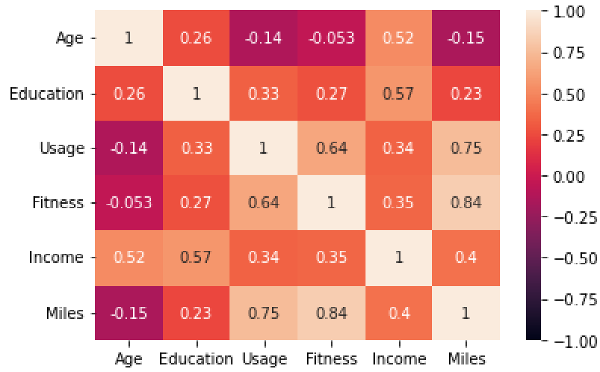
1. Females who purchased KP781 has planned the highest average number of miles per week and avg usage per week
2. We can influence this fact of planning high miles per week with intermediate level treadmill and upsell it to those females who purchased KP281.

```
avg_miles_female = sns.barplot(x=aerofit_female['Product'],y=aerofit_female['Miles'],estimator='mean')
avg_miles_female.bar_label(avg_miles_female.containers[0])
```

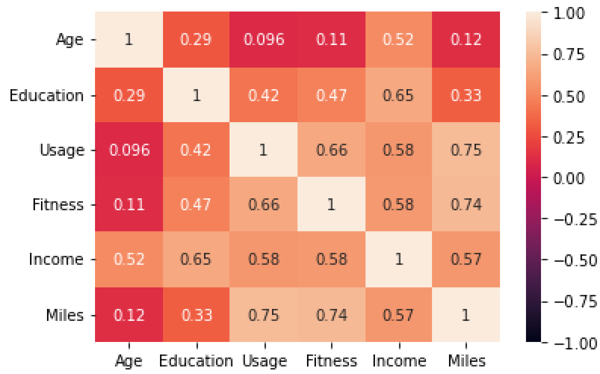
```
[Text(0, 0, '76.2'), Text(0, 0, '87.3448'), Text(0, 0, '180')]
```




```
heatmap_females = sns.heatmap(aerofit_female.corr(),vmin=-1,vmax=1,annot=True)
```




```
heatmap_males = sns.heatmap(aerofit_male.corr(),vmin=-1,vmax=1,annot=True)
```



Valuable Correlation

Mens income can indirectly effect the class of treadmill they buy. Like those who earn more income are more aged and also they are not intended to plan for more usage or miles in a week

Double-click (or enter) to edit

```
aerofit_female.Income.describe()
```

```
count       76.000000
mean     49828.907895
std      12557.690428
min      30699.000000
25%      42921.750000
50%      47754.000000
75%      53796.000000
max      95866.000000
Name: Income, dtype: float64
```

```
aerofit_female.Age.describe()
```

```
count    76.000000
mean     28.565789
std       6.342104
min      19.000000
25%      24.000000
50%      26.500000
75%      33.000000
max      50.000000
Name: Age, dtype: float64
```

```
aerofit_female
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
2	KP281	19	Female	14	Partnered	4	3	30699	66
5	KP281	20	Female	14	Partnered	3	3	32973	66
6	KP281	21	Female	14	Partnered	3	3	35247	75
9	KP281	21	Female	15	Partnered	2	3	37521	85
11	KP281	22	Female	14	Partnered	3	2	35247	66
...	...	...	...	...	...	...	...	...	...
152	KP781	25	Female	18	Partnered	5	5	61006	200
157	KP781	26	Female	21	Single	4	3	69721	100
162	KP781	28	Female	18	Partnered	6	5	92131	180
167	KP781	30	Female	16	Partnered	6	5	90886	280
171	KP781	33	Female	18	Partnered	4	5	95866	200

76 rows × 9 columns

```
female_buying_prob1 = pd.crosstab(index=aerofit_female['Product'],columns=aerofit_female['MaritalStatus'],margins=True)
female_buying_prob1
```

MaritalStatus	Partnered	Single	All
Product			
KP281	27	13	40
KP481	15	14	29
KP781	4	3	7
All	46	30	76

Key Facts

Probability of females buying different products

- The probability of buying **KP281 52.6%**
- The probability of buying **KP481 41.4%**
- The probability of buying **KP781 9.2%**

Probability of female with Single Status Buying following products

- The probability of buying **KP281 43.3%**
- The probability of buying **KP481 46.6%**
- The probability of buying **KP781 10.0%**

Probability of female with Partnered Status buying following products

- The probability of buying **KP281 58.6%**
- The probability of buying **KP481 32.6%**
- The probability of buying **KP781 8.6%**

```
Male_buying_prob1 = pd.crosstab(index=aerofit_male['Product'],columns=aerofit_male['MaritalStatus'],margins=True)
Male_buying_prob1
```

MaritalStatus	Partnered	Single	All
Product			
KP281	21	19	40
KP481	21	10	31
KP781	19	14	33
All	61	43	104

Key Facts

Probability of males buying different products

- The probability of buying **KP281 38.4%**
- The probability of buying **KP481 29.8%**
- The probability of buying **KP781 13.4%**

Probability of male with Single Status Buying following products

- The probability of buying **KP281 44.1%**
- The probability of buying **KP481 23.2%**
- The probability of buying **KP781 32.5%**

Probability of male with Partnered Status buying following products

- The probability of buying **KP281 34.4%**
- The probability of buying **KP481 34.4%**
- The probability of buying **KP781 31.1%**

```
pd.qcut(aerofit_female['Income'],q=4,labels=["I","II","III","IV"],retbins=True)
```

```
(2       I
 5       I
 6       I
 9       I
 11      I
        ..
 152    IV
 157    IV
 162    IV
 167    IV
 171    IV
 Name: Income, Length: 76, dtype: category
 Categories (4, object): ['I' < 'II' < 'III' < 'IV'],
 array([30699.  , 42921.75, 47754.  , 53796.  , 95866.  ]))
```

We have just made bins of the income using pd.qcut function to get more relation between the income and product purchased

We have created four BINS which go this way I,II,III,IV where I<II<II<III<IV and the values as shown below [30699. , 42921.75, 47754. , 53796. , 95866.]

```
female_income_BIN_1 = aerofit_female.loc[aerofit_female['Income']<= 42921.75]
female_income_BIN_1
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
2	KP281	19	Female	14	Partnered	4	3	30699	66
5	KP281	20	Female	14	Partnered	3	3	32973	66
6	KP281	21	Female	14	Partnered	3	3	35247	75
9	KP281	21	Female	15	Partnered	2	3	37521	85
11	KP281	22	Female	14	Partnered	3	2	35247	66
12	KP281	22	Female	16	Single	4	3	36384	75
13	KP281	22	Female	14	Single	3	3	35247	75
16	KP281	23	Female	14	Single	2	3	34110	103
18	KP281	23	Female	16	Single	4	3	38658	113
19	KP281	23	Female	15	Partnered	2	2	34110	38
22	KP281	24	Female	16	Single	4	3	42069	94
30	KP281	25	Female	14	Partnered	3	3	39795	85
32	KP281	25	Female	16	Partnered	2	2	40932	47
38	KP281	26	Female	16	Single	3	3	36384	66
67	KP281	37	Female	16	Partnered	3	3	37521	85
82	KP481	20	Female	14	Partnered	3	3	34110	106
84	KP481	21	Female	14	Partnered	5	4	34110	212
92	KP481	23	Female	14	Single	3	2	40932	53
94	KP481	24	Female	14	Single	3	2	40932	85

```
Female_income_bin1 = pd.crosstab(index=female_income_BIN_1['Product'],columns=female_income_BIN_1['MaritalStatus'],margi
Female_income_bin1
```

MaritalStatus	Partnered	Single
Product		
KP281	0.600000	0.400000
KP481	0.500000	0.500000
All	0.578947	0.421053

Interesting Fact-1

** Females with Income <= 40932$ has

1. The probability of buying KP281 40% for Singles and 60% for Partnered
2. The probability of buying KP481 50% for Singles and 50% for Partnered
3. **This income group (<=40932$) are not even showing interest to buy the advanced treadmill KP781 at all. So investing on marketing to this group of customers is not needed.**

```
female_income_BIN_2 = aerofit_female.loc[(aerofit_female['Income']>=40932) & (aerofit_female['Income']<= 47754.75) ]
female_income_BIN_2
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
22	KP281	24	Female	16	Single	4	3	42069	94
23	KP281	24	Female	16	Partnered	5	5	44343	188
26	KP281	24	Female	16	Single	4	3	46617	75
32	KP281	25	Female	16	Partnered	2	2	40932	47
34	KP281	26	Female	14	Partnered	3	4	44343	113
41	KP281	27	Female	14	Partnered	3	2	45480	66
43	KP281	27	Female	14	Partnered	2	3	45480	56
44	KP281	28	Female	14	Partnered	2	3	46617	56
51	KP281	29	Female	14	Partnered	2	2	46617	38
56	KP281	31	Female	14	Single	2	2	45480	47
57	KP281	32	Female	14	Single	3	4	46617	113
60	KP281	33	Female	16	Partnered	3	3	46617	85
89	KP481	23	Female	16	Single	3	3	45480	95
91	KP481	23	Female	16	Partnered	3	2	43206	74
92	KP481	23	Female	14	Single	3	2	40932	53
94	KP481	24	Female	14	Single	3	2	40932	85
97	KP481	25	Female	14	Partnered	2	3	45480	85
98	KP481	25	Female	14	Single	3	4	43206	127
100	KP481	25	Female	14	Partnered	5	3	47754	106
102	KP481	25	Female	14	Single	2	3	43206	64
106	KP481	25	Female	14	Single	2	2	45480	42
108	KP481	26	Female	16	Partnered	4	3	45480	85
114	KP481	30	Female	13	Single	4	3	46617	106

```
Female_income_bin2 = pd.crosstab(index=female_income_BIN_2['Product'],columns=female_income_BIN_2['MaritalStatus'],margi
Female_income_bin2
```

MaritalStatus	Partnered	Single
Product		
KP281	0.666667	0.333333
KP481	0.333333	0.666667
All	0.500000	0.500000

Interesting Fact-2

* *Females with Income > 40932* $and <= 47754$ has

1. The probability of buying KP281 33.3 % for Singles and 66.6% for Partnered
2. The probability of buying KP481 66.6 % for Singles and 33.3 % for Partnered
3. **This income group (<=40932$) are not even showing interest to buy the advanced treadmill KP781 at all. So investing on marketing to this group of customers is not needed.**

```
female_income_BIN_3 = aerofit_female.loc[(aerofit_female['Income']>47754) & (aerofit_female['Income']<= 53797) ]
female_income_BIN_3
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
27	KP281	25	Female	14	Partnered	3	3	48891	75
29	KP281	25	Female	14	Partnered	2	2	53439	47
35	KP281	26	Female	16	Partnered	4	3	52302	113
45	KP281	28	Female	16	Partnered	2	3	52302	66
49	KP281	28	Female	16	Partnered	3	3	51165	56
52	KP281	29	Female	16	Partnered	4	3	50028	94
62	KP281	34	Female	16	Single	2	2	52302	66
96	KP481	24	Female	16	Single	3	3	50028	106
109	KP481	26	Female	16	Single	4	4	50028	127
112	KP481	29	Female	14	Partnered	3	3	51165	95
116	KP481	31	Female	16	Partnered	2	3	51165	64
121	KP481	33	Female	16	Partnered	2	3	50028	85
123	KP481	33	Female	16	Partnered	5	3	53439	95
128	KP481	35	Female	14	Partnered	3	2	52302	53
130	KP481	35	Female	16	Single	3	2	50028	64
132	KP481	37	Female	16	Partnered	2	3	48891	85

```
Female_income_bin3 = pd.crosstab(index=female_income_BIN_3['Product'],columns=female_income_BIN_3['MaritalStatus'],margi
Female_income_bin3
```

MaritalStatus	Partnered	Single	All
Product			
KP281	6	1	7
KP481	6	3	9
KP781	0	2	2
All	12	6	18

Interesting Fact-3

* *Females with Income >47754*$and <= 53797$ has

1. The probability of buying KP281 14.2 % for Singles and .85.7% for Partnered
2. The probability of buying KP481 33.3 % for Singles and 66.6 % for Partnered
3. *This income group has 33.3% of total singles who are buying KP781 but 0% of the total Partners *

```
female_income_BIN_4 = aerofit_female.loc[(aerofit_female['Income']>52291) ]
female_income_BIN_4
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
29	KP281	25	Female	14	Partnered	2	2	53439	47
35	KP281	26	Female	16	Partnered	4	3	52302	113
45	KP281	28	Female	16	Partnered	2	3	52302	66
47	KP281	28	Female	14	Partnered	3	3	54576	94
59	KP281	33	Female	16	Single	2	2	55713	38
62	KP281	34	Female	16	Single	2	2	52302	66
64	KP281	35	Female	16	Partnered	3	3	60261	94
65	KP281	35	Female	18	Single	3	3	67083	85
69	KP281	38	Female	14	Partnered	2	3	54576	56
76	KP281	44	Female	16	Single	3	4	57987	75
77	KP281	46	Female	16	Partnered	3	2	60261	47
79	KP281	50	Female	16	Partnered	3	3	64809	66
113	KP481	30	Female	14	Single	3	3	57987	74
117	KP481	31	Female	18	Single	2	1	65220	21
123	KP481	33	Female	16	Partnered	5	3	53439	95
125	KP481	34	Female	16	Partnered	4	3	64809	95
128	KP481	35	Female	14	Partnered	3	2	52302	53

```
Female_income_bin4 = pd.crosstab(index=female_income_BIN_4['Product'],columns=female_income_BIN_4['MaritalStatus'],margi
Female_income_bin4
```

MaritalStatus	Partnered	Single
Product		
KP281	0.666667	0.333333
KP481	0.625000	0.375000
KP781	0.666667	0.333333
All	0.653846	0.346154

Interesting Fact-4

** Females with Income >52291$ has

1. The probability of buying KP281 33.3 % for Singles and .66.6% for Partnered
2. The probability of buying KP481 37.5 % for Singles and 62.5 % for Partnered
3. **This is the only income group where the probability of buying KP781 which is advanced treadmill with 33.3% of singles buying it and 66.6% of partnered buying**

```
pd.qcut(aerofit_male['Income'],q=4,labels=["I","II","III","IV"],retbins=True)
```

```
(0       I
 1       I
 3       I
 4       I
 7       I
        ..
 175    IV
 176    IV
 177    IV
 178    IV
 179    IV
 Name: Income, Length: 104, dtype: category
 Categories (4, object): ['I' < 'II' < 'III' < 'IV'],
 array([ 29562.  ,  45480.  ,  52302.  ,  61611.25, 104581.  ]))
```

```
male_income_BIN_1 = aerofit_male.loc[aerofit_male['Income']<= 45480]
male_income_BIN_1
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47
7	KP281	21	Male	13	Single	3	3	32973	85
8	KP281	21	Male	15	Single	5	4	35247	141
10	KP281	22	Male	14	Single	3	3	36384	85
14	KP281	23	Male	16	Partnered	3	1	38658	47
15	KP281	23	Male	16	Partnered	3	3	40932	75
17	KP281	23	Male	16	Partnered	4	3	39795	94
20	KP281	23	Male	14	Single	4	3	38658	113
21	KP281	23	Male	16	Single	4	3	40932	94
24	KP281	24	Male	14	Single	2	3	45480	113
25	KP281	24	Male	13	Partnered	3	2	42069	47
28	KP281	25	Male	14	Partnered	2	3	45480	56
31	KP281	25	Male	16	Single	3	4	40932	113
33	KP281	25	Male	16	Single	3	3	43206	85
39	KP281	26	Male	16	Partnered	4	4	44343	132
66	KP281	36	Male	12	Single	4	3	44343	94
80	KP481	19	Male	14	Single	3	3	31836	64
81	KP481	20	Male	14	Single	2	3	32973	53
83	KP481	20	Male	14	Single	3	3	38658	95
85	KP481	21	Male	16	Partnered	2	2	34110	42
86	KP481	21	Male	12	Partnered	2	2	32973	53
87	KP481	23	Male	14	Partnered	3	3	36384	95
88	KP481	23	Male	14	Partnered	3	3	38658	85
90	KP481	23	Male	16	Partnered	4	3	45480	127
93	KP481	23	Male	16	Partnered	3	3	45480	64
101	KP481	25	Male	14	Single	3	3	45480	95
103	KP481	25	Male	14	Partnered	4	3	45480	170
104	KP481	25	Male	14	Partnered	3	4	43206	106
111	KP481	27	Male	14	Single	4	2	45480	53

```
male_income_bin1 = pd.crosstab(index=male_income_BIN_1['Product'],columns=male_income_BIN_1['MaritalStatus'],margins=Tru
male_income_bin1
```

MaritalStatus	Partnered	Single
Product		
KP281	0.368421	0.631579
KP481	0.615385	0.384615
All	0.468750	0.531250

Interesting Fact in Male Customers -1

Males with Income >45480$ has

1. The probability of buying KP281 63.1 % for Singles and .36.8% for Partnered
2. The probability of buying KP481 38.4 % for Singles and 61.5 % for Partnered
3. **This income group has 0% of both singles and parterned who are buying KP781. So investing on marketing to this group of customers is not needed.**

```
male_income_BIN_2 = aerofit_male.loc[(aerofit_male['Income']>45480) & (aerofit_male['Income']<= 52302) ]
male_income_BIN_2
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
37	KP281	26	Male	16	Partnered	3	3	51165	85
40	KP281	26	Male	16	Single	3	3	50028	85
46	KP281	28	Male	14	Single	3	3	52302	103
53	KP281	30	Male	14	Partnered	4	4	46617	141
58	KP281	32	Male	14	Partnered	4	3	52302	85
61	KP281	34	Male	16	Single	4	5	51165	169
63	KP281	35	Male	16	Partnered	4	3	48891	85
68	KP281	38	Male	16	Partnered	3	3	46617	75
70	KP281	38	Male	14	Single	2	3	52302	56
95	KP481	24	Male	14	Single	3	4	48891	106
99	KP481	25	Male	16	Partnered	2	2	52302	42
105	KP481	25	Male	16	Partnered	2	3	50028	53
107	KP481	25	Male	14	Single	4	3	48891	127
110	KP481	26	Male	16	Single	4	3	51165	106
115	KP481	31	Male	16	Partnered	3	3	52302	95
122	KP481	33	Male	16	Partnered	3	3	51165	95
140	KP781	22	Male	14	Single	4	3	48658	106
142	KP781	22	Male	18	Single	4	5	48556	200
145	KP781	23	Male	16	Single	4	5	48556	100
149	KP781	24	Male	16	Single	5	5	49801	160
150	KP781	25	Male	16	Partnered	4	5	49801	120
165	KP781	29	Male	18	Single	5	5	52290	180

```
male_income_bin2 = pd.crosstab(index=male_income_BIN_2['Product'],columns=male_income_BIN_2['MaritalStatus'],margins=Tru
male_income_bin2
```

MaritalStatus	Partnered	Single
Product		
KP281	0.555556	0.444444
KP481	0.571429	0.428571
KP781	0.166667	0.833333
All	0.454545	0.545455

Interesting Fact in Male Customers -2

Males with Income >45480$ and <52302 has

1. The probability of buying KP281 44.4 % for Singles and .55.5% for Partnered
2. The probability of buying KP481 42.9 % for Singles and 57.1 % for Partnered
3. The probability of buying KP781 83.3% for singles and 16.6% for Partnered

```
male_income_BIN_3 = aerofit_male.loc[(aerofit_male['Income']>52302) & (aerofit_male['Income']<= 61611) ]
male_income_BIN_3
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
36	KP281	26	Male	16	Partnered	2	2	53439	47
42	KP281	27	Male	16	Single	4	3	54576	85
48	KP281	28	Male	14	Single	4	3	54576	113
54	KP281	30	Male	14	Single	3	3	54576	85
55	KP281	31	Male	14	Partnered	2	2	54576	47
71	KP281	38	Male	16	Partnered	3	3	56850	75
72	KP281	39	Male	16	Partnered	4	4	59124	132
73	KP281	40	Male	16	Partnered	3	3	61398	66
74	KP281	41	Male	16	Partnered	4	3	54576	103
75	KP281	43	Male	16	Partnered	3	3	53439	66
78	KP281	47	Male	16	Partnered	4	3	56850	94
118	KP481	32	Male	16	Single	4	3	60261	127
119	KP481	32	Male	16	Partnered	3	3	53439	95
120	KP481	33	Male	13	Partnered	4	4	53439	170
126	KP481	34	Male	16	Partnered	3	4	59124	85
129	KP481	35	Male	16	Partnered	3	2	53439	53
131	KP481	35	Male	16	Partnered	3	3	53439	95
134	KP481	38	Male	16	Partnered	3	3	59124	106
138	KP481	45	Male	16	Partnered	2	2	54576	42
139	KP481	48	Male	16	Partnered	2	3	57987	64
141	KP781	22	Male	16	Single	3	5	54781	120
143	KP781	23	Male	16	Single	4	5	58516	140
146	KP781	24	Male	16	Single	4	5	61006	100
147	KP781	24	Male	18	Partnered	4	5	57271	80

```
male_income_bin3 = pd.crosstab(index=male_income_BIN_3['Product'],columns=male_income_BIN_3['MaritalStatus'],margins=Tru
male_income_bin3
```

MaritalStatus	Partnered	Single
Product		
KP281	0.727273	0.272727
KP481	0.888889	0.111111
KP781	0.250000	0.750000
All	0.708333	0.291667

Interesting Fact in Male Customers -3

Males with Income >52302$ and <61611 has

1. The probability of buying KP281 27.2 % for Singles and .72.2% for Partnered
2. The probability of buying KP481 11.1 % for Singles and 88.8 % for Partnered
3. The probability of buying KP781 75.0% for singles and 25.0% for Partnered

```
male_income_BIN_4 = aerofit_male.loc[(aerofit_male['Income']>61611) ]
male_income_BIN_4
```

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
50	KP281	29	Male	18	Partnered	3	3	68220	85
127	KP481	34	Male	15	Single	3	3	67083	85
137	KP481	40	Male	16	Partnered	3	3	64809	95
151	KP781	25	Male	16	Partnered	4	4	62251	160
153	KP781	25	Male	18	Partnered	4	3	64741	100
154	KP781	25	Male	18	Partnered	6	4	70966	180
155	KP781	25	Male	18	Partnered	6	5	75946	240
156	KP781	25	Male	20	Partnered	4	5	74701	170
158	KP781	26	Male	16	Partnered	5	4	64741	180
159	KP781	27	Male	16	Partnered	4	5	83416	160
160	KP781	27	Male	18	Single	4	3	88396	100
161	KP781	27	Male	21	Partnered	4	4	90886	100
163	KP781	28	Male	18	Partnered	7	5	77191	180
164	KP781	28	Male	18	Single	6	5	88396	150
166	KP781	29	Male	14	Partnered	7	5	85906	300
168	KP781	30	Male	18	Partnered	5	4	103336	160
169	KP781	30	Male	18	Partnered	5	5	99601	150
170	KP781	31	Male	16	Partnered	6	5	89641	260
172	KP781	34	Male	16	Single	5	5	92131	150
173	KP781	35	Male	16	Partnered	4	5	92131	360
174	KP781	38	Male	18	Partnered	5	5	104581	150
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

```
male_income_bin4 = pd.crosstab(index=male_income_BIN_4['Product'],columns=male_income_BIN_4['MaritalStatus'],margins=Tru
male_income_bin4
```

MaritalStatus	Partnered	Single
Product		
KP281	1.000000	0.000000
KP481	0.500000	0.500000
KP781	0.739130	0.260870
All	0.730769	0.269231

Interesting Fact in Male Customers -4

Males with Income >61611$ has

1. **This group of customers has 0% probabity of buying the basic treadmill.Its not adviced to market about that product to this group of customers**
2. The probability of buying KP481 50.0 % for Singles and 50.0 % for Partnered
3. The probability of buying KP781 26.1% for singles and 73.9% for Partnered

0s completed at 9:04 PM